

A single perception can be used to represent many boolean functions (not xil)

A perception takes a vector of real-valued imputs, computes a linear combination

of these imputs, applies an activation function to it and returns the result.

Clarming means charing values for the weights Wo,..., Wn

 $E(w) = \frac{1}{2} \sum_{m=1}^{N} (\xi_m - \xi_m)^2 - \frac{1}{2} \sum_{m=1}^{N} (\xi_m)^2$ Contribution of the weight w; in E(w): ground touth

we want to minimize E(w)

 $\frac{\partial \mathcal{E}_{\partial W_{i}}}{\partial w_{i}} = \frac{1}{2} \sum_{m=1}^{N} \frac{\partial w_{i}}{\partial w_{i}} (t_{m} - w^{T} \times_{m})^{2} = \frac{1}{2} \sum_{m=1}^{N} Z(t_{m} - w^{T} \times_{m}) \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) = \sum_{m=1}^{N} (t_{m} - w^{T} \times_{m}) (-x_{i,m}) \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) = \sum_{m=1}^{N} (t_{m} - w^{T} \times_{m}) \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) \frac{\partial w_{i}}{\partial w_{i}} \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) \frac{\partial}{\partial w_{i}} (t_{m} - w^{T} \times_{m}) \frac{\partial w_{i}}{\partial w_{i}} \frac{\partial}{\partial w_{i}} \frac{\partial}{\partial w_{i}} \frac{\partial w_{i}}{\partial w_$ 

we can use this derivative (gradient) to implement an iterative approach to find the new value

W: Wi - D SEW: Learning rate, low much to move

This procedure can fail to converge if we get stuck on a local minima w:
This update rule (gradient descent) provides the basis for the backpropagation (used in naturals with many interconnected wits)

repeat until termination condition (error < E) Considering all the samples can be very hard

■ Batch mude → consider all the dataset D → DWi = p [(t - D(x)) Xi

■ Mlini-batch mode -- choose a small subset SCD -- DW: = p [(+ - o(x)) x;

■ We cremental mode - choose one sample (x,t) ∈ 5 - DWi = p(t-o(x)) xi

Termination conditions:

■ predefined number of iterations

 threshold on changes in the loss function E(w) Morever the learning rate p should be sufficiently small; if we choose a large learning rate the new error value could be even ligger

N.B. moving with small p (learning rate) the solution will be very dose to some samples in the dataset